Biological Contagion

Principles of Complex Systems
CSYS/MATH 300, Fall, 2010

Prof. Peter Dodds

Department of Mathematics & Statistics
Center for Complex Systems
Vermont Advanced Computing Center
University of Vermont

Outline

Introduction

Simple disease spreading models
Background
Prediction
More models
Toy metapopulation models
Model output
Conclusions
Predicting social catastrophe

References

Contagion

A confusion of contagions:

- Is Harry Potter some kind of virus?
- What about the Da Vinci Code?
- Does Sudoku spread like a disease?
- Religion?
- Democracy...?

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Naturomorphisms

- "The feeling was contagious."
- "The news spread like wildfire."
- "Freedom is the most contagious virus known to man."
  —Hubert H. Humphrey, Johnson's vice president
- "Nothing is so contagious as enthusiasm."
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The doctrine that everything is beautiful, including what is ugly, everything good, especially the bad, and everything right that is wrong. ...

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The doctrine that everything is beautiful, including what is ugly, everything good, especially the bad, and everything right that is wrong. ... It is hereditary, but fortunately not contagious.

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Eric Hoffer, 1902–1983

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The spread of fanaticism

Hoffer's acclaimed work: "The True Believer: Thoughts On The Nature Of Mass Movements" (1951) [3]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the passion of a small minority."

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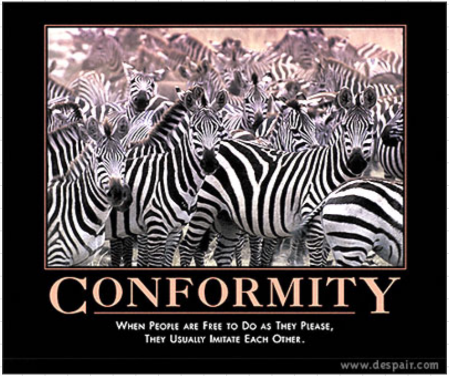
Imitation

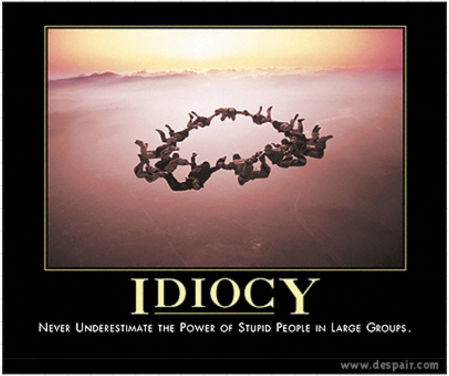


despair.com

"When people are free to do as they please, they usually imitate each other."

—Eric Hoffer
"The Passionate State of Mind" [4]

The collective...



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"Never Underestimate the Power of Stupid People in Large Groups."

Contagion

Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- from Latin: *con* = ‘together with’ + *tangere* ‘to touch.’
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The UNIVERSITY of VERMONT

Examples of non-disease spreading:

Interesting infections:

- Spreading of buildings in the US. (⊞)
- Viral get-out-the-vote video. (⊞)

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Two main classes of contagion

1. Infectious diseases
2. Social contagion

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   tuberculosis, HIV, ebola, SARS, influenza, ...
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Two main classes of contagion

1. Infectious diseases:
   tuberculosis, HIV, ebola, SARS, influenza, ...

2. Social contagion:
   fashion, word usage, rumors, riots, religion, ...

Outline

Mathematical Epidemiology

The standard SIR model [8]

- = basic model of disease contagion
- Three states:
  1. S = Susceptible
  2. I = Infective/Infectious
  3. R = Recovered or Removed or Refractory
- $S(t) + I(t) + R(t) = 1$
- Presumes random interactions (mass-action principle)
- Interactions are independent (no memory)
- Discrete and continuous time versions

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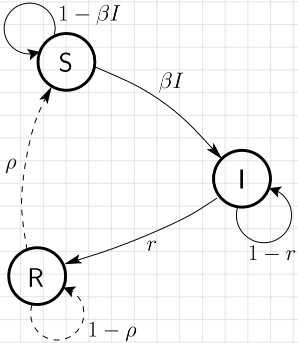
Discrete time automata example:



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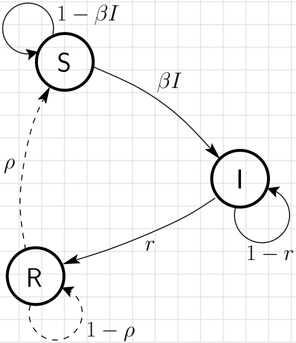

Transition Probabilities:

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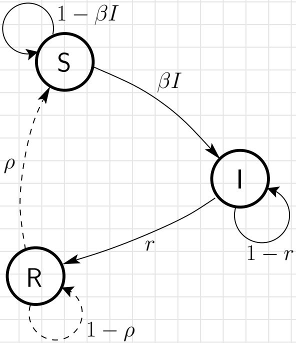

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β for being infected given contact with infected

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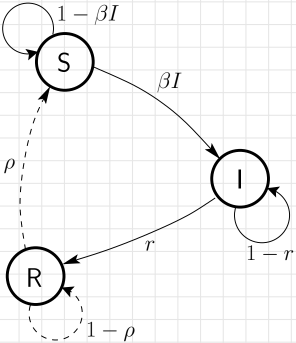

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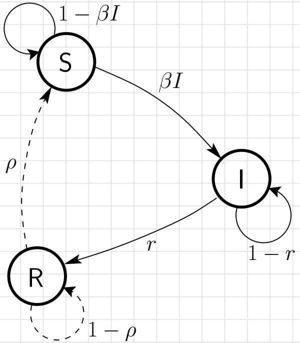

Transition Probabilities:

β for being infected given contact with infected
r for recovery
ρ for loss of immunity

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Original models attributed to

- 1920's: Reed and Frost
- 1920's/1930's: Kermack and McKendrick [5, 7, 6]
- Coupled differential equations with a mass-action principle

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Independent Interaction models

Differential equations for continuous model

$$\frac{\mathrm{d}}{\mathrm{d}t} S = -\beta IS + \rho R$$

$$\frac{\mathrm{d}}{\mathrm{d}t} I = \beta IS - rI$$

$$\frac{\mathrm{d}}{\mathrm{d}t} R = rI - \rho R$$

β, r, and ρ are now rates.

Reproduction Number R_0:

- R_0 = expected number of infected individuals resulting from a single initial infective
- Epidemic threshold: If $R_0 > 1$, 'epidemic' occurs.

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Discrete version:

- Set up: One Infective in a randomly mixing population of Susceptibles
- At time $t = 0$, single infective random bumps into a Susceptible
- Probability of transmission = β
- At time $t = 1$, single Infective remains infected with probability $1 - r$
- At time $t = k$, single Infective remains infected with probability $(1 - r)^k$

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- Expected number infected by original Infective:

$$R_0 = \beta + (1 - r)\beta + (1 - r)^2\beta + (1 - r)^3\beta + \ldots$$

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For S_0 initial infectives ($1 - S_0 = R_0$ immune):

$$R_0 = S_0\beta/r$$

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For the continuous version

- Second equation:

$$\frac{\mathrm{d}}{\mathrm{d}t} I = \beta S I - r I$$

- Number of infectives grows initially if

$$\beta S(0) - r > 0$$

- Same story as for discrete model.

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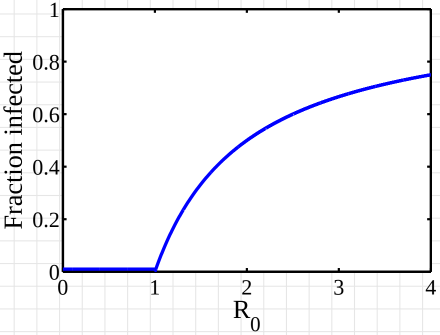

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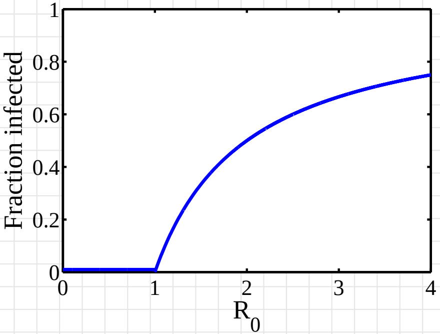

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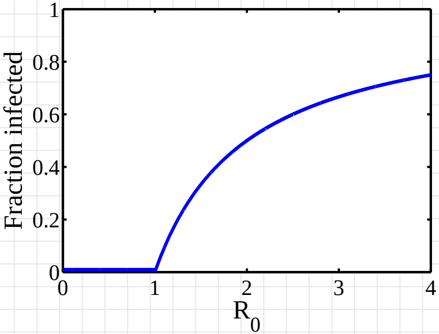

- Continuous phase transition.
- Fine idea from a simple model.

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Many variants of the SIR model:

- SIS: susceptible-infective-susceptible
- SIRS: susceptible-infective-recovered-susceptible
- compartment models (age or gender partitions)
- more categories such as ‘exposed’ (SEIRS)
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Disease spreading models

For novel diseases:

1. Can we predict the size of an epidemic?
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R_0 and variation in epidemic sizes

R_0 approximately same for all of the following:

- 1918-19 “Spanish Flu” $\sim$ 500,000 deaths in US
- 1957-58 “Asian Flu” $\sim$ 70,000 deaths in US
- 1968-69 “Hong Kong Flu” $\sim$ 34,000 deaths in US
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Size distributions are important elsewhere:

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- city sizes, forest fires, war fatalities
- wealth distributions
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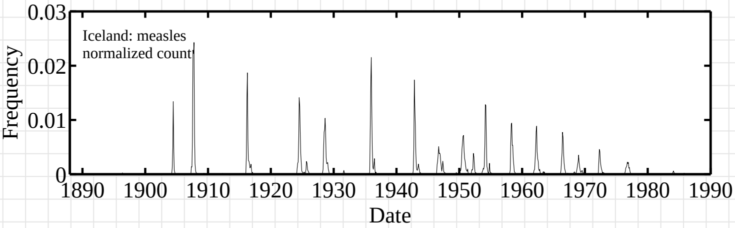
Feeling Ill in Iceland

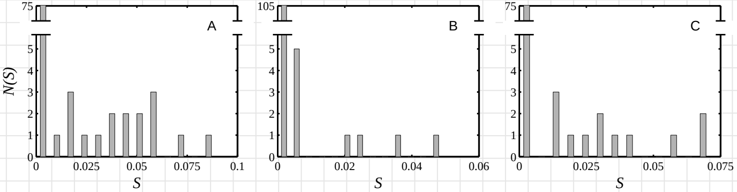
Caseload recorded monthly for range of diseases in Iceland, 1888-1990



- Treat outbreaks separated in time as 'novel' diseases.

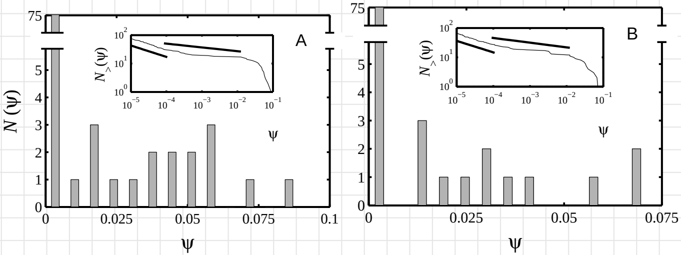
Really not so good at all in Iceland

Epidemic size distributions $N(S)$ for Measles, Rubella, and Whooping Cough.



Spike near $S = 0$, relatively flat otherwise.

Measles & Pertussis



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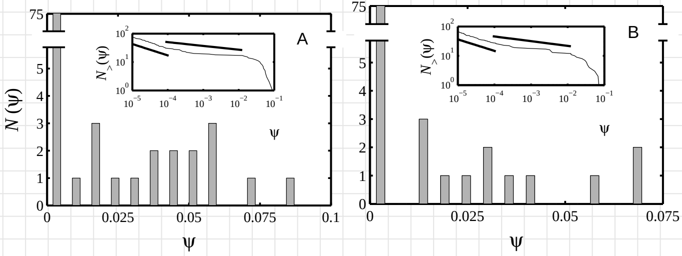

Insert plots:

Complementary cumulative frequency distributions:

$$N(\Psi' > \Psi) \propto \Psi^{-\gamma+1}$$

Limited scaling with a possible break.

Power law distributions

Measured values of γ:

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)

- Expect $2 \leq \gamma < 3$ (finite mean, infinite variance)
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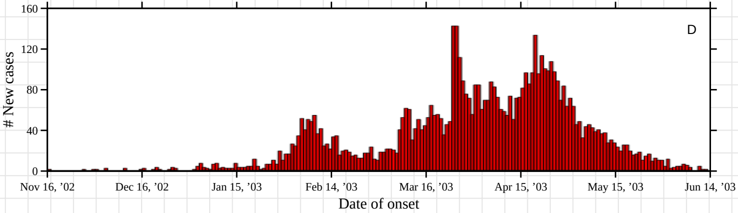

- Epidemic slows...
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- Importance of rare, stochastic events.

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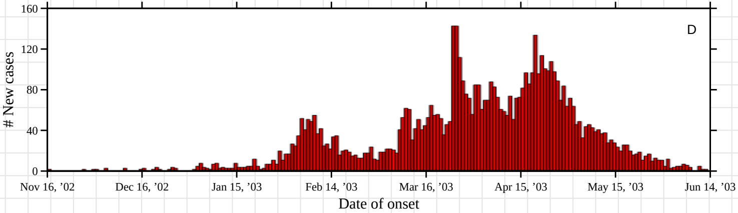

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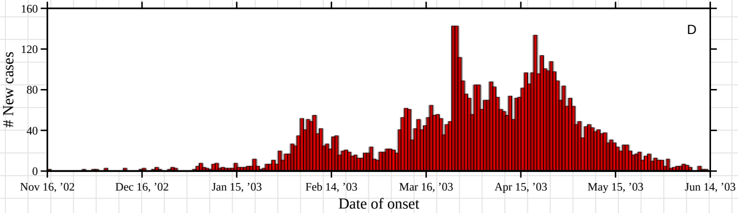

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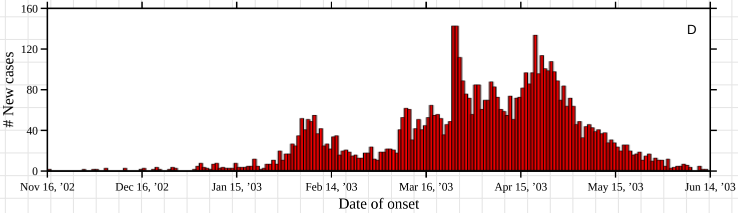

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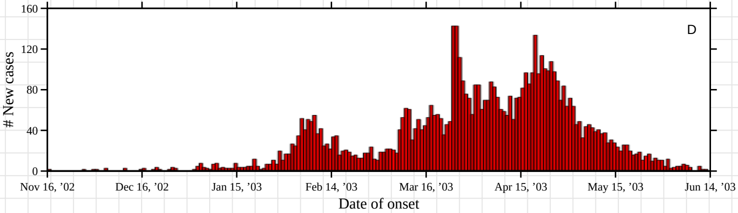

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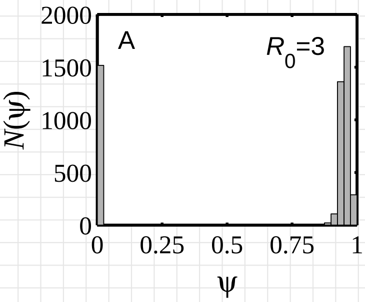
The challenge

So... can a simple model produce

1. broad epidemic distributions
   and
2. resurgence ?

Size distributions



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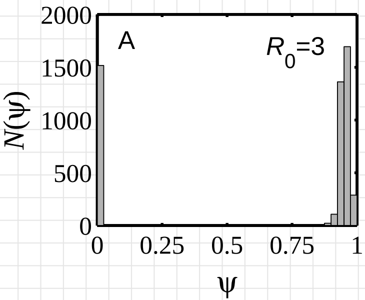

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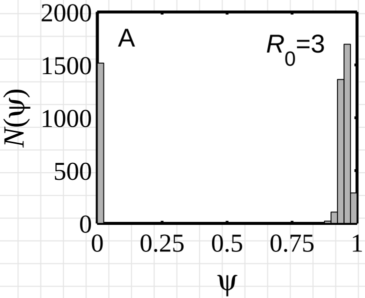

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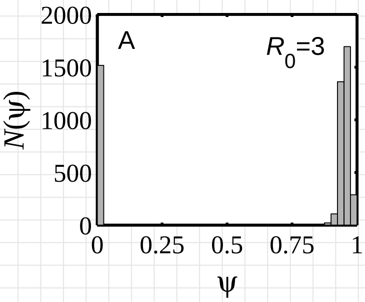

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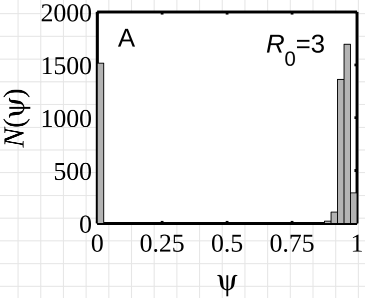

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Burning through the population

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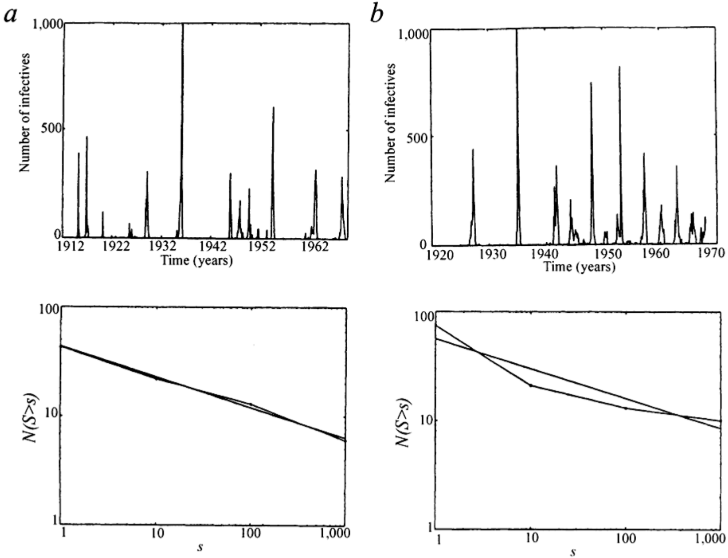

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- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
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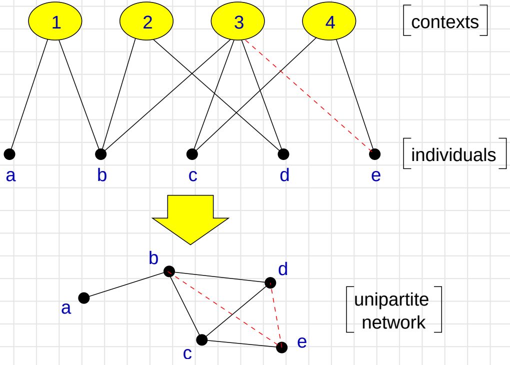

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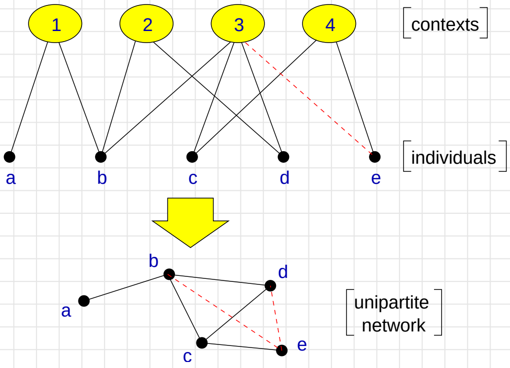

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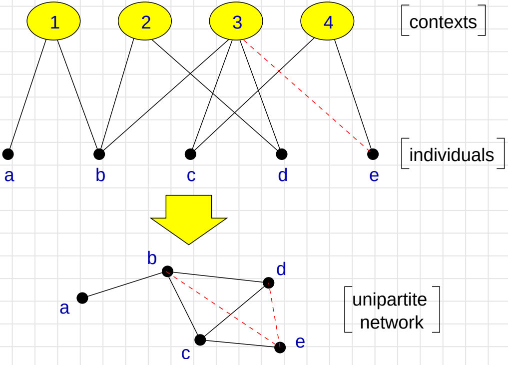

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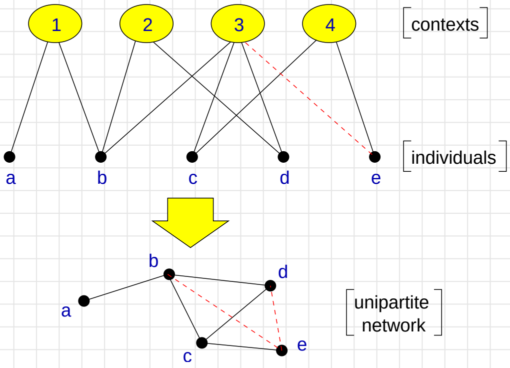

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Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

- Geographic location
- Type of employment
- Age
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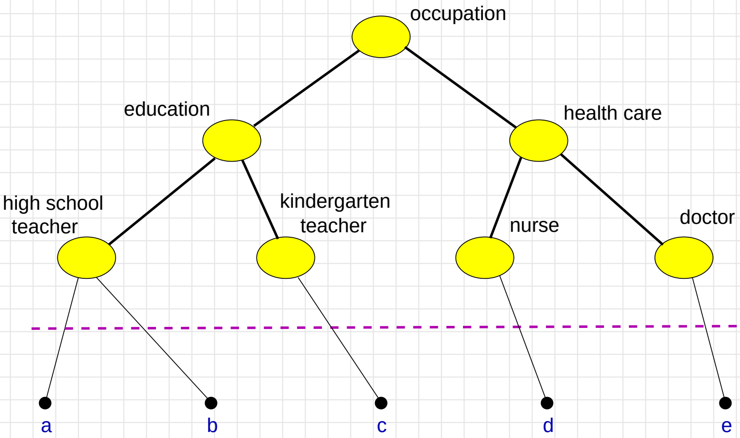
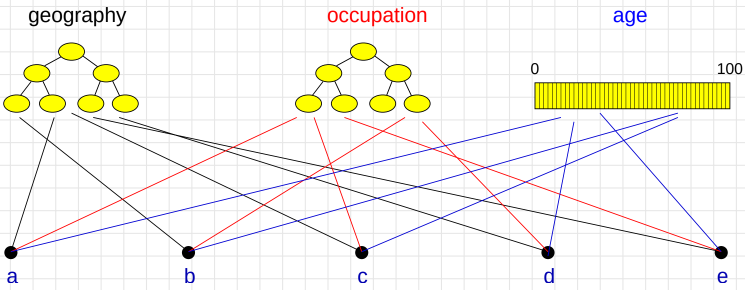
Infer interactions/network from identities



Distance makes sense in identity/context space.

Generalized context space



(Blau & Schwartz [1], Simmel [10], Breiger [2])

A toy agent-based model

Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- β = infection probability
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The UNIVERSITY of VERMONT

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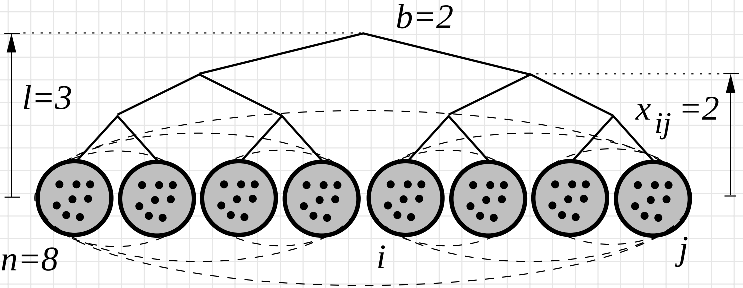
Schematic:



Outline

Model output

- Define P_0 = Expected number of infected individuals leaving initially infected context.
- Need $P_0 > 1$ for disease to spread (independent of R_0).
- Limit epidemic size by restricting frequency of travel and/or range

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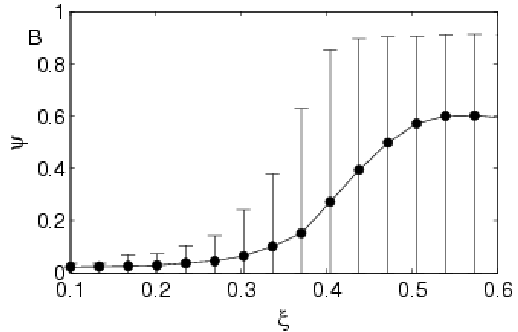
Model output

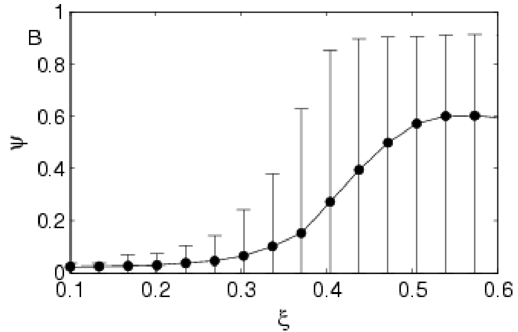
Varying ξ:



- Transition in expected final size based on typical movement distance

Model output

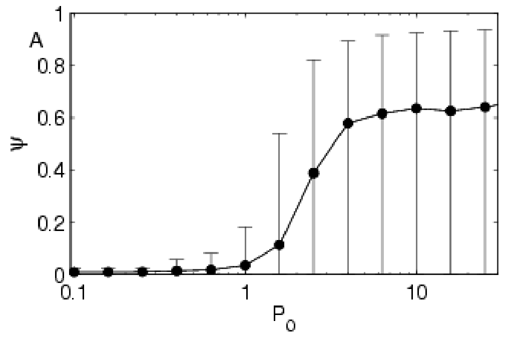
Varying ξ:



- Transition in expected final size based on typical movement distance (sensible)

Model output

Varying P_0:



- Transition in expected final size based on typical number of infectives leaving first group
- Travel advisories: ξ has larger effect than P_0.

Model output

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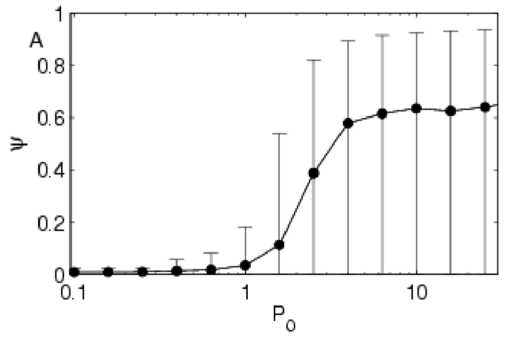

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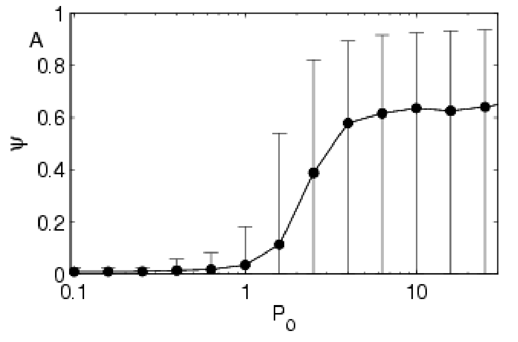

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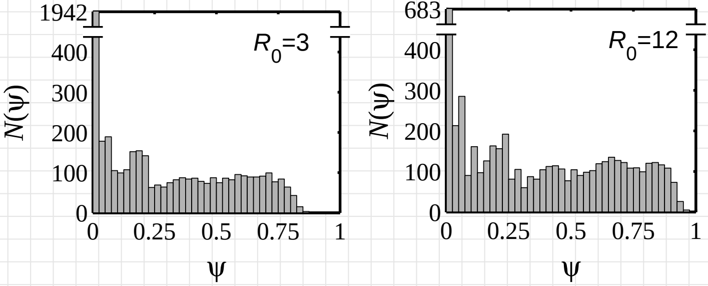
Example model output: size distributions



- Flat distributions are possible for certain ξ and P.
- Different R_0's may produce similar distributions
- Same epidemic sizes may arise from different R_0's

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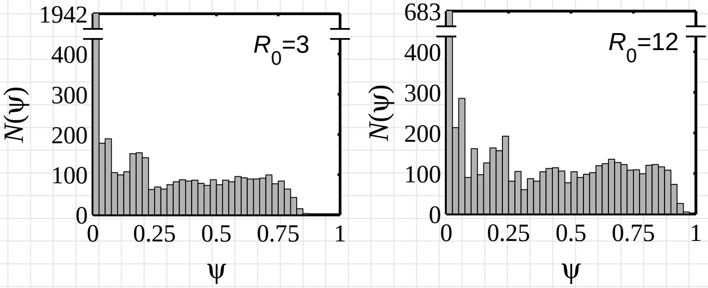

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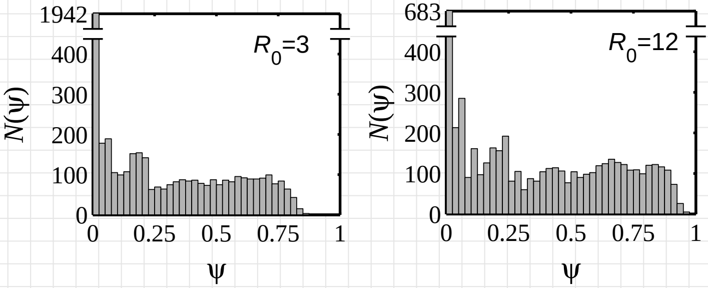

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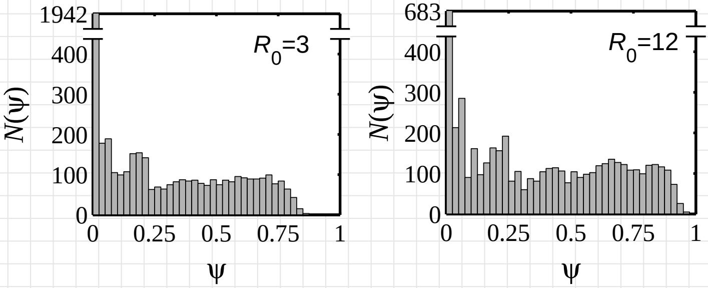

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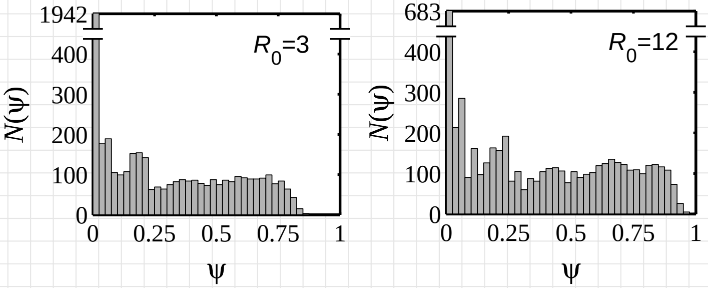

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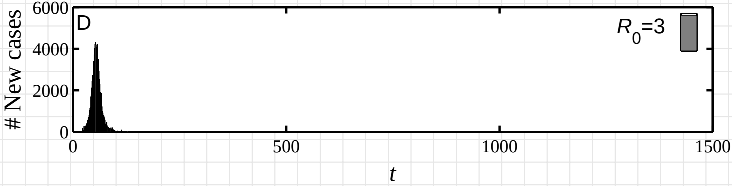
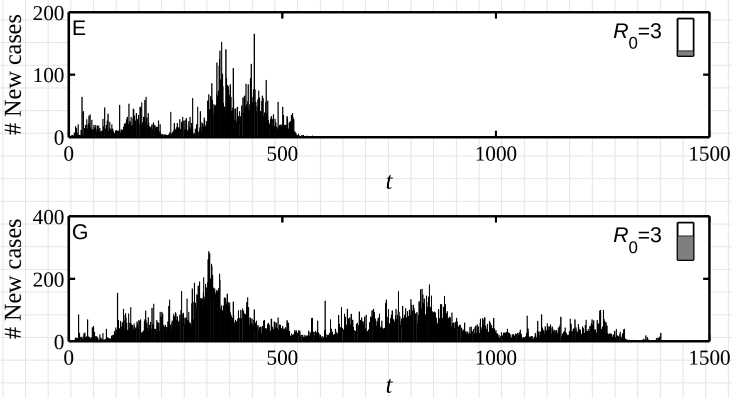
Model output—resurgence

Standard model:



Model output—resurgence

Standard model with transport:



The upshot

Simple multiscale population structure

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Simple multiscale population structure

+

stochasticity

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leads to

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broad epidemic size distributions

Outline

Conclusions

- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- The reproduction number R_0 is not terribly useful.
- R_0, however measured, is not informative about
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More wondering:

- Exactly how important are rare events in disease spreading?
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Jon Stewart:

"You just bummed the @*!# out of me."

wildbluffmedia.com

- From the Daily Show (⊞) (September 18, 2007)
- The full inteview is here (⊞).

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